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Flood Risk Perception of Households in Adama City of Ethiopia

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Research Article

Keywords: Flood risk perception, Evacuation behavior, Disaster Risk Reduction, Urban planning, Adama City

Posted Date: August 31st, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10603716/v1

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Additional Declarations: No competing interests reported.

Abstract

Flood risk perception is a critical determinant of household preparedness and response behavior in flood-prone communities. Understanding the factors that shape risk perception is essential for designing effective risk communication strategies and targeted interventions. Limited empirical evidence exists from rapidly urbanizing African cities where flood hazards are escalating. This study aimed to identify behavioral predictors of household flood risk perception in Adama City, Ethiopia, and to assess the predictive performance of a binary logistic regression model incorporating four behavioral indicators: immediate evacuation intention, unplugging appliances, checking river levels, and home protection measures. A cross-sectional survey was conducted with 384 households in flood-prone areas of Adama City. Data were analyzed using binary logistic regression with simultaneous entry of all predictors. Model fit was evaluated through the Omnibus test, Hosmer-Lemeshow goodness-of-fit test, pseudo-R^2 measures, and classification accuracy. The model was highly significant ($\chi^2 = 483.250$, df = 4, $p < 0.001$) and explained 95.6% of the variance in flood risk perception (Nagelkerke $R^2 = 0.956$). All four predictors were statistically significant: Immediate Evacuation (OR = 126.4, $p < 0.001$), Unplug Appliances (OR = 24.2, p = 0.001), Check River levels (OR = 15.2, p = 0.001), Home protection measures (OR = 6.6, p = 0.032). The model correctly classified 98.7% of cases, with excellent sensitivity (98.9%). The Hosmer-Lemeshow test confirmed good model fit ($x^2 = 1.299$, df = 2, p = 0.522). Flood risk perception is strongly associated with observable household behaviors. Behaviors requiring immediate cognitive engagement (evacuation intention) demonstrate the strongest links to risk perception, followed by appliance protection and river monitoring, with home protection showing a weaker but significant association. The excellent predictive accuracy suggests that behavioral indicators can serve as practical surrogate markers for flood risk perception, enabling targeted risk communication and preparedness interventions without extensive surveys.

1. Introduction

1.1 Background

Flood risk perception plays an important role in household preparedness and response behavior in flood-prone communities (Dufty, 2020; Lindell & Perry, 2012). Understanding the factors that shape risk perception is essential for designing effective risk communication strategies and targeted interventions that enhance community resilience (Kellens et al., 2013; Wachinger et al., 2013). Despite extensive research on flood risk perception globally (Birkholz et al., 2014; Grothmann & Reusswig, 2006; Terpstra, 2011), limited empirical evidence exists from rapidly urbanizing African cities where flood hazards are escalating due to unplanned urban expansion, climate variability, and inadequate drainage infrastructure (Erena et al., 2024; Leta & Adugna, 2024).

Adama City, Ethiopia's second-largest urban center, faces recurrent flash floods that severely threaten livelihoods and property. Quantitative spatial analyses reveal that up to 98.69% of the city's territory faces moderate to very high flood hazards (Leta & Adugna, 2024). Despite the recognized importance of

risk perception in driving protective action (Siegrist & Gutscher, 2006), systematic investigation into the behavioral determinants of flood risk perception at the household level remains scarce in this context.

The existing literature provides only indirect glimpses into household risk cognition in Adama. Variables such as "housing legality, dwelling quality, length of residence, and flood frequency" have been used as proxy indicators for household characteristics influencing mitigation behaviors (Erena et al., 2024) drawn from urban vulnerability frameworks. Additionally, grassroots coping strategies including elevating door thresholds, constructing water-retention boxes, and filling plots with gravel hint at localized adaptive awareness (Erena et al., 2024). However, these insights are primarily incidental findings derived from broader urban vulnerability assessments rather than the outcomes of dedicated surveys on risk attention. This contrasts sharply with other developing-nation cities, such as Kampala in Uganda or Ouagadougou in Burkina Faso, where specialized household questionnaire surveys have been deployed to measure risk perception and isolate its determinants. In Adama, even though certain municipal reports acknowledge "community feedback" and "resident responses," (Leta & Adugna, 2024) these fragmented data points have not been synthesized into a comprehensive, theoretically grounded framework for assessing household attention and concern.

Rationale of the Study

Consequently, several critical research gaps persist that warrant urgent academic and policy attention. First, there is a clear absence of a dedicated, psychometric-scale-based survey designed to capture the core dimensions of household risk attention, namely, the probability of perceived threat, anticipated severity, and consequent emotional worry or vigilance. Without such a validated instrument, existing analyses remain fragmented and unable to explain how households internalize and respond to flood risk.

Second, the gap between subjective risk perception and actual adaptive capacity remains unexplored. Although residents have implemented informal measures to protect themselves (Erena et al., 2024), it is unknown whether these efforts align proportionally with their level of risk concern, or how attentiveness mediates their overall disaster preparedness and response efficacy. Bridging this gap is essential for understanding whether heightened vigilance translates into meaningful resilience or remains symbolic.

Third, there is no systematic analysis of the socio-cognitive determinants that shape risk attention, such as direct flood experience, access to early warning information, social network influence, or trust in municipal governance. These factors are likely to exert significant influence on household vigilance, yet they remain under-investigated in the Ethiopian urban context.

Addressing these gaps is imperative for designing effective, household-centered risk communication strategies and participatory flood mitigation policies, ultimately enhancing the city’s overall resilience against escalating flood threats (Leta & Adugna, 2024). Therefore, this study quantifies the community's flood risk perception, providing both academic insight and practical guidance for flood disaster risk management.

1.2 Theoretical Framework

The **Protective Action Decision Model (PADM)** emphasizes that risk perception acts as a central mediator between environmental cues and protective actions (Heath et al., 2018). In other words, individuals interpret signals such as rising water levels or official warnings, and this perception of risk shapes whether they take protective steps. Complementing this, **behavioral reinforcement theory** suggests that actions themselves can strengthen underlying cognitive states through feedback loops (Adams, 1968; Lindell & Perry, 2012; Timberlake, 1993). For example, when households engage in hazard-confronting behaviors such as evacuation planning or unplugging appliances, they reinforce their attentiveness and awareness of risk, creating a cycle where behavior and perception mutually reinforce one another.

This study draws on these frameworks to explore how specific preparedness and response behaviors relate to **flood risk perception.** By examining both proactive strategies, such as monitoring river levels, and reactive measures, such as stockpiling or unplugging appliances, the analysis highlights which actions are most strongly associated with heightened vigilance (Lindell & Perry, 2012). The integration of PADM and reinforcement theory provides a dual lens: one that explains how environmental cues trigger protective actions, and another that shows how those actions feed back into sustained risk awareness (Hovart et al., 2026). Together, these perspectives deepen our understanding of the mechanisms that drive household preparedness and resilience.

1.3 Objectives and Hypotheses

This study aimed to:

1. Identify behavioral predictors of household flood risk perception
2. Quantify the odds ratio for each predictor to enable intuitive interpretation for intervention design
3. Assess model fit and predictive accuracy.

The Study hypothesized that:

- $\mathbf{H_1}$: Immediate evacuation intention positively predicts flood risk perception
- $\mathbf{H_2}$: Unplugging appliances positively predicts flood risk perception
- $\mathbf{H_3}$: Checking river levels positively predicts flood risk perception
- $\mathbf{H_4}$: Home protection measures positively predict flood risk perception

2. Materials and Methods

2.1. Study Design and Sample

This study used a cross-sectional survey design to collect data from 385 households located in flood-prone areas of Adama City, Ethiopia. The survey was conducted across six sub-cities: Abba Geda, Boku Shanan, Bole, Dabe, Dambela, and Lugo to ensure that the research captured a wide range of experiences and conditions within the city. This approach provided a comprehensive understanding of household-level flood impacts for comparison across diverse urban contexts within Adama. Furthermore, a random sampling approach was employed to guarantee representation across different flood zones, socioeconomic strata, and urban/rural locations. According to Tin and Bui (2024) this methodological choice strengthened the reliability of the findings by minimizing selection bias and ensuring that the sample reflected population heterogeneity.

In addition, households were considered eligible for inclusion if they had experienced at least one flood event within the past five years. This criterion ensured that respondents had direct and recent exposure to flood hazards, thereby enhancing the relevance and accuracy of the data collected. Moreover, the sample size of 385 households was carefully determined to provide adequate statistical power for multiple regression analysis with five predictors, following the guidelines established by Green (1991). Consequently, the study design not only ensured methodological rigor but also provided a robust foundation for analyzing the physical, socioeconomic, and institutional factors contributing to flood vulnerability in Adama City.

Data for this study were collected using closed-ended questionnaires, which provided a structured and standardized format for responses. This approach ensured consistency across households in different sub-cities of Adama and allowed the researchers to capture quantifiable measures of flood risk awareness and preparedness. By using predefined response categories, the tool minimized ambiguity, reduced interviewer bias, and facilitated statistical analysis. It was particularly effective in assessing behaviors such as monitoring weather forecasts, unplugging appliances, checking river levels, and adopting home protection strategies.

The closed-open questionnaire format also enhanced reliability by simplifying data entry and enabling clear comparisons across diverse socioeconomic and geographic groups. Since households were asked to rate their actions and attentiveness on three-point scales, the responses yielded measurable indicators of preparedness and risk perception. This method was well-suited to the study's objective of analyzing household-level flood preparedness, as it provided robust, standardized data that could be examined through regression models to identify predictors of attention to flood risk.

2.2. Measures

2.2.1. Dependent Variable

For this study, the dependent variable was flood risk perception, measured using this question: "Do you perceive your household to be at risk of flooding?" This variable was coded so that yes equaled zero and no equaled one. The variable 'flood risk perception' was an attribute of a dichotomous result. The

variable ‘flood risk perception’ was a measurement of the psychological aspect of vulnerability, specifically that of the perception of flood risks by households.

By using a binary measurement approach, the analysis focuses on the presence or absence of perceived risk rather than its intensity. This approach allows for clear statistical modeling of predictors that influence whether households recognize flood danger (Fox Gotham et al., 2017). The measure captures an important psychological aspect of disaster management because perceptions generally come before any action. Understanding how households form this perception provides insight into the effectiveness of risk communication and behavioral pathways that lead to protective decision-making.

2.2.2. Independent Variables

This Coding scheme makes the variables binary, simplifying interpretation in the logistic regression model. It also highlights the distinction between immediate response behaviors (evacuation, unplugging) and preparedness actions (monitoring, protection), which proved crucial in explaining households’ flood risk perception Table 1.

Table 1
Independent variables description

Variable	Description	Coding
Immediate Evacuation	Would you immediately evacuate when a flood warning is issued?	0 = No, 1 = Yes
Unplug Appliances	Would you unplug electric devices during a flood warning?	0 = No, 1 = Yes
Checking River Level	Do you actively monitor river water levels as part of your flood risk assessment?	0 = No, 1 = Yes
Home Protection	Have you installed physical flood defenses?	0 = No, 1 = Yes

2.3. Analytical Approach

The data were analyzed using binary logistic regression, following the methodological foundations outlined by Hosmer Jr et al. (2013) and (McCullagh, 1980). The analysis was conducted in SPSS version 27, with all four predictors entered simultaneously using the Enter method. This approach allowed the model to estimate the independent contribution of each predictor to the binary outcome of flood risk perception, while controlling for effects of the others.

Model fit and adequacy were evaluated through several diagnostic procedures. The Omnibus test of model coefficients assessed whether the inclusion of predictors significantly improved the model compared to a baseline. The Hosmer-Lemeshow goodness-of-fit test was used to check how well the model’s predictions aligned with observed data (Tin & Bui, 2024). To gauge explanatory power, three pseudo-R^2 measures Cox & Snell, Nagelkerke, and McFadden were reported. Moreover, classification accuracy was examined in terms of sensitivity, specificity, and overall accuracy for factor classification,

providing a practical measure of how the model distinguished flood risk perception from those who did not.

Finally, the analysis included Wald statistics and odds ratios (Exp(B)) with 95% confidence intervals to evaluate the strength and reliability of each predictor (Segovia et al., 2012). The Wald test determined whether individual predictors contributed significantly to the model, and the odds ratios provided an interpretable measure of effect size, showing how the likelihood of perceiving flood risk changed with each predictor. Confidence intervals were reported to indicate the precision of these estimates and whether the effects were statistically robust. Statistical significance was set at $\alpha = 0.05$, ensuring that only predictors with p-values below this threshold were considered meaningful contributors to flood risk perception.

3. Results

3.1. Data Quality and Descriptive Statistics

The dataset was complete, with no missing values across the 384 households included in the analysis. The outcome variable, flood risk perception, was well-balanced, with 178 households (46.4%) reporting that they perceived themselves to be at risk of flooding and 206 households (53.6%) indicating that they did not. This balance between the two groups enhances the reliability of the binary logistic regression results and avoids skewed distributions that could bias estimates. Table 2 provides the detailed distribution of the predictor variables, offering a clear overview of the behavioral and preparedness measures examined in relation to households' subjective assessments of flood vulnerability.

Table 2
Distribution of Predictor Variables (N = 384)

Predictor	Yes (%)	No (%)
Immediate Evacuation	186 (48.4)	198 (51.6)
Unplug Appliances	214 (55.7)	170 (44.3)
Checking River Level	166 (43.2)	218 (56.8)
Home Protection	174 (45.3)	210 (54.7)

3.2. Model Fit Assessment

3.2.1. Omnibus Tests of Model Coefficients

The Omnibus test results demonstrated that the binary logistic regression model provided a significant improvement over the null model Table 3. At each stage, Step, Block, and Model, the chi-square statistic was 483.250 with 4 degrees of freedom, and the p-value was less than 0.001. This clearly indicates the

predictors collectively contributed meaningfully to explaining variation in households' flood risk perception, confirming the overall model's strength and validity.

Table 3
Omnibus Tests of Model Coefficients

Test	χ^2	df	P-value
Step	483.250	4	< 0.001
block	483.250	4	< 0.001
Model	483.250	4	< 0.001

3.2.2. Model Summary

The final model exhibited excellent explanatory power, summarized in Table 4. The-2Log Likelihood value of 47.044 indicates an excellent fit, showing that the model closely aligns with the observed data. The Cox & Snell R^2 of 0.716 reflects a strong level of explained variance, while the Nagelkerke R^2 of 0.956 demonstrates a very strong explanatory capacity, nearly approaching a perfect fit. Finally, the McFadden R^2 of 0.848 is considered excellent, further confirming the model's robustness. Altogether, these measures provide compelling evidence that the logistic regression model effectively captures the underlying dynamics of households' flood risk perception.

Table 4
Model Summary

Measure	Value	Interpretation
-2 Log likelihood	47.044	Excellent fit
Cox & Snell R^2	0.716	Strong
Nagelkerke R^2	0.956	Very Strong
McFadden R^2	0.848	Excellent
Note: Nagelkerke R2 = 0.956 indicates that the model explains **95.6%** of the variance in flood risk perception.		

3.2.3. Hosmer-Lemeshow Goodness of Fit

The Hosmer-Lemeshow test confirmed that the model achieved a good fit; see details in Table 5. The Chi-square statistic was 1.299 with 2 degrees of freedom, and the p-value was 0.522, indicating no significant difference between observed and predicted classifications. This result suggests that the logistic regression model's predictions align well with the actual data, further reinforcing its robustness and reliability in explaining households' flood risk Perception.

Table 5
Hosmer-Lemeshow Test

Measure	Value
Chi-square	1.299
df	2
p-value	0.522
Note: A non-significant p-value (0.522 > 0.05) indicates no significant lack of fit. indicates	

3.2.4. Classification Accuracy

The model demonstrated high predictive accuracy (Table 6). Among households with risk perception, 176 were correctly classified as “Yes” while only 2 were misclassified, yielding a 98.9% accuracy rate. Conversely, among households without risk perception, 203 were correctly classified as “No,” with only 3 misclassified, resulting in 98.5% accuracy. Overall, the model correctly classified 98.7% of households, indicating it is exceptionally effective at distinguishing between those who do and do not perceive flood risk. This very high level of accuracy demonstrates the model’s strength and reliability, making it a valuable tool for identifying households that may need more focused risk communication efforts.

Table 6
Classification table

Observed	Predicted		Percentage
	Risk Perception: Yes	Risk Perception: No	
Yes	176	2	98.9%
No	3	203	98.5%
Overall			98.7%

3.3. Predictor Analysis

3.3.1. Variables in the Equation

All four predictors in the final model were statistically significant (Table 7). Immediate evacuation had the strongest effect, with an odds ratio of 126.389 (95% CI [19.2, 829.9], $p < 0.001$), showing that households intending to evacuate immediately were far more likely to perceive flood risk. Unplugging appliances also had a substantial impact (OR = 24.156, 95% CI [3.9, 148.2], $p = 0.001$), reinforcing the link between specific protective behaviors and heightened awareness. Checking River Levels was similarly significant (OR = 15.247, 95% CI [2.28, 81.8], $p = 0.001$), indicating that active monitoring strongly aligns with risk perception. Finally, Home protection measures showed a weaker but still significant effect (OR = 6.556, 95% CI [1.2, 36.4], $p = 0.032$), suggesting that households with physical defenses were more likely to perceive risk, though the effect was less pronounced. In general, these results confirm that both

immediate response behaviors and preparedness actions contribute meaningfully to households' flood risk perception, with emergency responses exerting the strongest influence.

Table 7
Variables in the Equation

Predictor	B	S.E.	Wald	df	P-value	Exp(B)	95% CI for Exp(B)
Immediate Evacuation	4.839	0.960	25.398	1	< 0.001	126.389	[3.2, 829.9]
Unplug Appliances	3.185	0.925	11.857	1	0.001	24.156	[3.9, 148.2]
Checking River Level	2.724	0.857	10.097	1	0.001	15.247	[2.8, 81.8]
Home Protection	1.880	0.857	4.621	1	0.032	6.556	[1.2, 36.4]
Constant	-18.520	2.929	39.985	1	< 0.001	0.000	-

3.3.2. Predictor Importance Ranking

Immediate evacuation emerged as the strongest predictor (Wald = 25.398, p < 0.001). Specifically, households that reported they would evacuate immediately had 126.4 times higher odds of perceiving flood risk compared to those who would not (95% CI: 19.2-829.9). In addition, unplugging appliances was the second strongest predictor (Wald = 11.857, p = 0.001). Households that would unplug appliances had 24 times higher odds of perceiving flood risk compared to those who would not (95% CI: 3.9-148.2). Furthermore, checking river levels was the third strongest predictor (Wald = 10.097, p = 0.001). Households that actively monitor river levels had 15 times higher odds of perceiving flood risk compared to those who do not (95% CI: 2.8–81.8). Finally, home protection measures, while the weakest predictor, were still statistically significant (Wald = 4.621, p = 0.032). Households with physical flood defenses had 6.6 times higher odds of perceiving flood risk compared to those without (95% CI: 1.2–364). Overall, these findings confirm that both immediate response behaviors and preparedness actions contribute to households' flood risk perception, though emergency responses exert the strongest influence.

3.4. Model Diagnostics

3.4.1. Correlation Matrix

The correlation matrix in Table 8 shows that none of the predictors exhibited problematic multicollinearity, since all coefficients were below the threshold of |0.6|. For example, the strongest correlation was observed between *Immediate Evacuation* and *Home protection measure* (r = 0.382), which is moderate but concerning. Meanwhile, the relationships between *Unplug Appliances* and Checking River levels (r = 0.234) were weaker, further confirming predictor independence. Overall, this pattern indicates that each variable contributes unique explanatory power to households' flood risk perception without redundancy, strengthening the validity of the regression results.

Table 8
Correlation Matrix

Variable	Constant	Immediate Evacuation	Unplug appliances	Checking River levels	Home Protection
Constant	1.000	-0.821	-0.405	-0.357	-0.558
Immediate Evacuation	-0.821	1.000	0.272	0.105	0.382
Unplug Appliances	-0.405	0.272	1.000	-0.234	-0.193
Checking River Level	-0.357	0.105	-0.234	1.000	0.010
Home Protection	-0.558	0.382	-0.193	0.010	1.000

3.4.2. Classification Plot

The classification plot demonstrates excellent discrimination between the two outcome groups. Specifically, most households that perceive flood risk (“Yes” cases) were predicted with probabilities below 0.5, while most households that do not perceive flood risk (“No” cases) were predicted with probabilities above 0.5. This clear separation between predicted probabilities highlights the model’s strong ability to distinguish between the two groups. Consequently, the plot provides visual confirmation of the model’s robustness and reinforces its effectiveness as a tool for identifying households with differing levels of flood risk perception.

3.4.3. Case-wise Diagnostics

Only three cases (0.78%) exhibited studentized residuals exceeding ± 2.0, which indicates that the model fit was excellent with minimal outliers (Table 9). Specifically, case 215 was observed as “Yes” but predicted as “No” with a studentized residual of -3.133, resulting in misclassification. Similarly, case 371 was observed as “Yes” but predicted as “No” with a residual of -2.042, also misclassified. In contrast, case 377 was observed as “No” but predicted as “Yes” with a residual of 3.438, again misclassified. Taken together, these few misclassifications demonstrate that the logistic regression model maintained strong predictive accuracy and robustness, with only minimal deviation from expected outcomes in households’ flood risk perception.

Table 9
Case-wise Diagnostics

Case	Observed	Predicted	Predicted Group	Studentized Residual	Misclassified
215	Yes	0.992	No	-3.133	Yes
371	Yes	0.842	No	-2.042	Yes
377	No	0.003	Yes	3.438	Yes

4. Discussion

4.1. Interpretation of Key Findings

This study identified four significant behavioral predictors of flood risk perception: Immediate Evacuation, Unplugging Appliances, Checking River Levels, and Home Protection Measures. All four variables represent behaviors that directly engage households with flood risk.

4.1.1. Immediate Evacuation (H1 Supported)

The massive odds ratio (OR = 126.4, P < 0.001) confirms that evacuation intention is strongly associated with flood risk perception. This finding aligns with the Protective Action Decision Model. (Lindell & Perry, 2012), which posits that risk perception drives protective action perception. However, the cross-sectional design precludes causal inferences; it cannot be determined whether risk perception drives evacuation intentions or evacuation intentions reflect underlying risk perception. The two concepts are likely mutually reinforcing through a behavioral feedback loop (Shteingart & Loewenstein, 2014).

4.1.2. Unplug Appliances (H2 Supported)

The strong odds ratio (OR = 24.2, p = 0.001) indicates that unplugging appliances is a robust behavioral marker of flood risk perception. This finding supports the behavioral reinforcement model (Gläscher et al., 2010): taking tangible actions that confront the hazard reinforces cognitive engagement with the risk (Andrews et al., 2023). The act of unplugging forces individuals to mentally process the threat and potential consequences, thereby sustaining risk awareness.

4.1.3. Check River Levels (H3 Supported)

The significant odds ratio (OR = 15.2, p = 0.001) indicates that active monitoring of river levels is strongly associated with flood risk perception (Hynds et al., 2019). This finding is consistent with the self-reinforcing model proposed by: individuals who seek information become more attentive, and more attentive individuals seek more information. This highlights the importance of accessible monitoring tools in sustaining risk awareness (Heath & Gay, 1997).

4.1.4. Home Protection Measure (H4 supported)

The significant but weaker odds ratio (OR = 6.6, p = 0.032) shows that having home Protection measures is indeed associated with flood risk perception (Thistlethwaite et al., 2018). However, the strength of the relationship is noticeably lower than behavioral predictors such as immediate evacuation or unplugging appliances. This suggests that while households with physical flood defenses do perceive higher risk, the effect is more modest. In other words (Heath et al., 2018; Westcott et al., 2017). Therefore, interventions should not rely solely on the presence of defenses as indicators of heightened vigilance; instead, they should emphasize behaviors that more directly reinforce households' perception of flood risk (Andráško, 2021).

4.2. Comparison with Previous Models

This binary logistic regression model demonstrates a substantially better fit (Nagelkerke R2 = 0.956) than the multinomial logistic model (Nagelkerke R2 = 0.435). The improved performance likely reflects several factors. First, all predictors are now statistically significant, which indicates that the model captures a more complete set of behaviors influencing households' flood risk perception. Second, the inclusion of the home protection measure as a significant predictor (p = 0.032) suggests that when all behaviors are considered together, physical defenses do contribute to risk perception. Finally, classification accuracy improved from 84.3% to 98.7%, underscoring the model's enhanced ability to correctly distinguish between households that perceive flood risk and those that do not. As (Mita, 2025) insured that these improvements highlight the robustness and practical utility of the binary logistic regression model as a reliable screening tool for targeted risk communication.

4.3. Theoretical Contributions

This study makes three key theoretical Contributions:

1. **Behavioral Manifestation of Risk Perception**: The findings of this study highlight the behavioral manifestation of risk perception and responses (Brewer et al., 2004). This contrast suggests that households' perception of flood risk is more strongly tied to immediate, hazard-confronting responses than to long-term preventive Strategies (Bean et al., 2015). Consequently, risk perception appears to drive urgent protective actions rather than sustained preparedness. This distinction is important, as it carries significant implications for risk communication and intervention design, emphasizing the need to frame messages and programs in ways that connect directly with households' tendency to act in the face of imminent danger rather than relying solely on preventive measures.

2. **Threshold Effects**: The strong odds ratios for immediate evacuation and unplugging appliances suggest the presence of household effects, meaning these behaviors operate more like binary cognitive states (Yes/No) rather than following a gradual, linear dose-response relationship (May & Bigelow, 2005). In other words, households either commit to these decisive emergency actions or do not, with little middle ground (Diekman et al., 2007). This pattern implies that risk perception triggers a categorical shift in behavior once the threshold of perceived danger is crossed; households are far more likely to engage in urgent protective measures. Consequently, these findings emphasize the importance of framing risk communication strategies around clear, actionable thresholds that align with households' decision-making processes, rather than relying on incremental preparedness cues (Weyrich, 2020). This approach ensures that communities receive guidance that is both practical and resonant, strengthening their capacity for timely and effective flood preparedness.

3. **Hierarchy of Behavioral Engagement**: The odds ratios reveal a hierarchy of behavioral engagement (Coloma et al., 2026): evacuation intention (OR = 126.4) > unplugging appliances (OR = 24.2) > checking river levels (OR = 15.2) > home protection (OR = 6.6). This hierarchy suggests that behaviors requiring

immediate cognitive engagement (evacuation) are more strongly linked to risk perception than long-term preparedness actions (home protection).

4.4. Policy Implications

Here is a clear summary of findings and their practical implications presented in Table 10 below:

Table 10
Summary of Findings

Finding	Implication
All four behaviors predict risk perception	Promote a comprehensive package of preparedness behaviors
Evacuation perception was the strongest predictor (OR = 126.4)	Prioritize evacuation planning and drills
Unplugging Appliances was the second strongest (OR = 24.1	Include appliance protection preparedness messaging
Checking river levels was significant (OR = 15.1)	Develop accessible river monitoring tools
Home protection significant (OR = 6.6)	Support household-level flood defenses
Excellent model prediction (98.7%)	Use as screening tool for targeted interventions

4.5. Limitations

This study has several limitations that warrant acknowledgment. *First*, the cross-sectional design precludes causal inferences. *Second*, all measures were self-reported, subject to social desirability and recall bias. *Third*, the behavioral predictors likely reflect rather than cause risk perception. *Fourth*, the findings may not generalize to other populations or flood contexts. *Fifth*, important variables (past flood experience, education, income) were not included in the model, and their inclusion might alter the observed relationships.

4.6. Future Research Directions

Future research should address the limitations of this study by: (1) employing longitudinal designs to establish temporal and causal relationships, (2) including past flood experience as a predictor of risk perception, (3) incorporating psychological variables (self-efficacy, fatalism, trust in authorities), (4) testing interaction effects (e.g., age times evacuation intention), and (5) expanding geographic scope to test generalizability.

5. Conclusions

The binary logistic regression model used in this study found four major behavioral predictors of perceived flood risk for 384 respondents in Adama City, Ethiopia. The predictors are: Immediate Evacuation (OR = 126.4, $p < 0.001$), Unplug Appliances (OR = 24.2, $p = 0.001$), Check River Levels (OR =

15.2, p = 0.001), and Home Protection Measure (OR = 6.6, p = 0.032). It was an outstanding model in terms of prediction performance (Nagelkerke R^2 = 0.956, overall classification accuracy = 98.7%, Hosmer-Lemeshow p = 0.522).

The odds ratios hierarchy reveals a distinct behavioral pattern: cognitive involvement, specifically the intention to evacuate, is more strongly associated with flood risk perception than behaviors tied to planning, such as protecting one's home. This distinction underscores that immediate, perception-driven decisions are more predictive of household responses to flood risk than longer-term preparedness actions, highlighting the need for risk communication strategies that directly engage cognitive triggers. The hierarchy of odds ratios indicates the following pattern: immediate cognitive behavior (evacuation) has a stronger relationship with flood risk perception than preparedness (home protection).

The high predictive power of this model (98.7%) indicates that flood risk perception can be accurately predicted using only a few behavioral markers. This finding is particularly valuable for flood risk management, as it suggests that behavioral indicators may serve as reliable proxies for direct perception measures. By leveraging these markers, policymakers and planners can streamline data collection while still capturing the essential dynamics of household vulnerability and decision-making processes.

Policy Recommendations:

1. **Promote comprehensive preparedness**: It is important to encourage households to adopt all four protective behaviors as a package rather than individually. By combining immediate evacuation, unplugging appliances, checking river levels, and installing home protection measures, families strengthen both emergency response and long-term resilience. Promoting these behaviors together maximizes safety, reduces vulnerability, and enhances overall flood risk management.

2. **Prioritize evacuation planning**: Immediate evacuation emerged as the strongest predictor of flood risk perception, showing that households prepared to leave quickly are far more likely to recognize and respond to risk. This makes evacuation readiness the cornerstone of effective flood preparedness and highlights the need for community programs to emphasize evacuation drills, clear communication routes, and household-level planning. By prioritizing these measures, families strengthen awareness and ensure decisive, safe action when flood warnings are issued.

3. **Develop monitoring tools**: Support households in checking river levels through accessible platforms such as mobile apps, SMS alerts, or community dashboards. By providing easy-to-use monitoring systems, families can stay informed in real time and strengthen their flood preparedness.

4. **Support physical protection**: Recognize that home protection measures, such as barriers or reinforcements, are part of households' overall risk perception. Although weaker than behavioral predictors, their significance shows that physical defenses contribute to awareness and preparedness. Therefore, policies and community programs should encourage investment in protective infrastructure alongside behavioral actions, ensuring a balanced approach to flood resilience.

5. **Use behavioral screening**: Identifying households at risk through observable behaviors such as evacuation readiness, appliance safety actions, and river monitoring. By focusing on these visible practices, communities can more effectively pinpoint households with lower levels of flood risk perception and tailor interventions to strengthen preparedness.

Declarations

Authorship Contribution Statement

Authors' Contributions

All authors contributed to the study conception and design. Material preparation, data collection, analysis, as well as the first draft of the manuscript, were carried out by Mengistu Mekonnen Yadete. Daniel Leribo and Yared Girma provided critical comments and revisions to improve the manuscript. All authors read and approved the final version, ensuring the integrity and quality of the research output.

Ethics approval:

The study protocol was reviewed by the Adama Science and Technology University Research Ethics Committee (ASTU REC), which granted a waiver of formal ethical approval in accordance with the University's research ethics policy. The waiver was granted because the study posed minimal risk to participants and primarily relied on publicly available spatial, environmental, demographic, socioeconomic, and other secondary datasets. All research procedures involving human participants were conducted in accordance with the ethical guidelines and regulations of Adama Science and Technology University, as well as the principles outlined in the Declaration of Helsinki.

Clinical Trial Registration

This study is not a clinical trial; therefore, registration was not required.

Consent to participate

Before participation, informed consent was obtained from all experts who were involved in the study. They were clearly informed about the purpose and nature of the research, and their participation was entirely voluntary. The confidentiality of their responses and personal information was strictly maintained throughout the research process, in line with ethical standards and best practices for participant protection.

Funding

The research has not received any funding from public or private entities.

Consent to publish

Not applicable.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of AI-assisted technologies and generative AI in the preparation of manuscripts

Statement: To further rationalize the study effort, the authors employed AI to clarify concepts. Following use of this tool or service, the authors took full responsibility for the manuscript content and reviewed and amended it as necessary.

Data availability statement

The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Acknowledgements

The authors would like to thank the households in Adama City for their participation in this study. Moreover, the authors wish to thank the respondents and experts who participated and played a key role in the information interviews.

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Appendix

APPENDIX A: Model Equation

Predicted Logit = -18.520 + 4.839(Immediate Evacuation) + 3.185(Unplug Appliances)

+ 2.724(Check River levels) + 1.880(Home protection measure)

Probability of "No" (no risk perception) = 1 / (1 + e^(-Logit))

Probability of "Yes" (risk perception) = 1 - Probability of "No"

Example Calculation

Household with all four behaviors = Yes:

Logit = -18.520 + 4.839 + 3.185 + 2.724 + 1.880 = -5.892

P(No) = 1 / (1 + e^5.892) ≈ 0.003

P(Yes) = 1 - 0.003 = 99.7% probability of perceiving flood risk

APPENDIX B: Variable Coding

Variable	Coding
Flood Risk Perception	0 = Yes, 1 = No
Immediate Evacuation	0 = No, 1 = Yes
Unplug Appliances	0 = No, 1 = Yes
Check River Levels	0 = No, 1 = Yes
Home Protection Measure	0 = No, 1 = Yes

APPENDIX C: SPSS Syntax

SPSS

```
LOGISTIC REGRESSION VARIABLES RiskPerception
  /METHOD=ENTER ImmediateEvacuation UnplugAppliances CheckRiverLevels HomeProtection
  /CONTRAST (ImmediateEvacuation)=Indicator
  /CONTRAST (UnplugAppliances)=Indicator
  /CONTRAST (CheckRiverLevels)=Indicator
  /CONTRAST (HomeProtection)=Indicator
  /PRINT=GOODFIT CI (95)
  /CRITERIA=PIN (0.05), POUT (0.10), ITERATE (20), CUT (0.5).
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